

An Empirical Analysis of Remote Sensing Teaching Innovations in Postgraduate Built Environment Education

Nor Aizam Binti Adnan*, Ainon Nisa Othman, Zaharah Mohd Yusoff

Surveying Science and Geomatic, Faculty of Built Environment, Universiti Teknologi MARA

*Corresponding Author

DOI: <https://doi.org/10.47772/IJRISS.2026.102100067>

Received: 09 July 2026; Accepted: 14 July 2026; Published: 24 July 2026

ABSTRACT

Although remote sensing is an important part of the curriculum for students of built environment, traditional classroom-based courses may not be able to keep up with the pace of modern geospatial technologies in the industry, and students are not equipped with the skills needed by professionals in the field. To solve this problem, an innovative teaching model was adopted in the teaching of MSc remote sensing course Remote Imaging and Processing (GES 713), which combined the advanced technology tools such as satellite data analysis and machine learning image processing with practical applications in true platforms. Students did not merely study theory but faced real-world data challenges that were directly related to industry and the local community and had them present a two-step presentation to industry and academic member – a first. This method was very successful as shown by feedback from 40 students in a questionnaire. The collaborative, tech-driven approach proved to be much more effective (Mean = 4.50) than traditional lectures, and students indicated that that exposure to advanced machine learning and satellite datasets helped to increase their confidence to enter the geospatial workforce (Mean = 4.38). They strongly suggested that other advanced STEM courses should implement this community engaged design (Mean = 4.45), and that transforming intricate technical information for two completely different audiences effectively honed their flexibility in communicating (Mean = 4.05). In conclusion, this research demonstrates that integration of contemporary technological innovation and community-based, experiential learning is very effective in preparing postgraduate students to be job-ready and provides an effective and practical approach to deliver geospatial education in the future.

Keywords: Remote sensing, teaching, innovation, student feedback

INTRODUCTION

The utilization of remote sensing and geospatial technologies is a crucial skill for addressing difficult urban and climate problems, especially as the built environment rapidly evolves (Mašterová, 2023). This has put a strain on the Master of Science (MSc) programmes to ensure that their graduates possess adequate spatial thinking and technical skills (Mkhongi & Musakwa, 2020). But the conventional classroom system remains largely based on passive teaching and learning, and it is not always possible to provide students with authentic hands-on experiences. This leaves a frustrating situation for students as they are introduced to these geospatial tools but rarely engage in using them to solve real world urban problems (DeMers et al., 2021). This has led to a huge disconnect between what is taught in the classroom and what is required for the workplace, particularly in the sense of communicating technical information to various audiences.

To resolve this problem, recent studies proposed that the subjects of advanced STEM courses should be more concerned by the experience of learning and work in the real world (Do et al., 2023). Students who are actively engaged with the content of their courses are also better team players, more prepared for the workforce and are very much more connected to the academic environment when the courses enable direct links to industry and to local communities (Mendo-Lázaro et al., 2022). This research builds on this concept, and examines a new pedagogical approach implemented in an MSc course on Remote Sensing in the Faculty of Built Environment. Through analysing the feedback from the students in the questionnaire, the impact of the pairing of a practical

and experiential project with a novel two-step presentation format (industry presentation and academic lecture, in class) was observed. In summary, we hope that these reflections will provide a practical guideline for future remote sensing courses to enable students to develop technical skills and practical flexibility with communication in the real world.

LITERATURE REVIEW

The introduction of new technologies in the built environment necessitates constant adaptation of the remote sensing courses; the most effective way to teach remote sensing is to focus on software training in an interactive and hands-on manner. Instead of teacher-centred lectures, the use of web-based programming and interactive geospatial tools helps to overcome high technical barriers and helps students to manipulate real-world satellite visualizations on their own (Li et al., 2020). This pedagogical change addresses the disconnect between the current higher education landscape and the rapidly changing needs of the spatial information workforce by combining fundamental concepts and regional case studies (Bauer et al., 2021). In addition, the inclusion of extensive laboratory experiments and data manipulation activities directly within the post-graduation courses encourages pupils' curiosity and enhances their capabilities of technical problem-solving (Abekiri et al., 2023). In conclusion, the implementation of such innovations in education is essential for modernizing course structures, coping with new developments in the field of data analytics, and preparing master's students for full job readiness in the geospatial industry (Chasmer et al., 2021).

This software simulation can have maximum impact with collaboration from industrial teams that bring classroom activities to life in real landscapes. MSc students in Malaysia will have access to real-life scenarios of precision agriculture by integrating the institutional knowledge and professional practices of major agricultural organizations, such as the Malaysian Palm Oil Board (MPOB), the Malaysia Cocoa Board (MCB) and the Malaysia Agricultural Research and Development Institute (MARDI). For example, in the study of long-term agricultural spatial trends, students will be able to follow the spatial expansion of crops on a large scale and understand the economic impact of geospatial data in real life (Li et al., 2020). Exposure to cutting-edge monitoring technologies, like drone surveys and artificial intelligence, offers students insights into the industry's management of plantation well-being and its disease surveillance on a commercial level (Akhtar et al., 2023). Furthermore, synthesising the data of both active radar and passive optical satellite data in a framework of industries will enable students to fill in the missing data and cross check with national agricultural statistics from official sources (Mohd Najib et al., 2020; Nuthammachot, 2022).

In addition to management of agriculture, geospatial solutions are crucial for the urbanisation process, and curricula related to the built environment must closely relate to the national planning bodies, such as PLANMalaysia. Official spatial planning policies can be incorporated in student project works, and the postgraduates can use Landsat and high-resolution satellite imagery to create a comprehensive Land Use and Land Cover (LULC) maps and analysis (Ghalehtemouri et al., 2024). The practical alignment is essential for identifying a local microclimate threat, such as the urban heat island effect and monitoring the land surface temperature change and its relation to land surface cover change (Ebrahimian & Nurrudin, 2024). Furthermore, hands-on application of the real physical planning frameworks in the study of satellite data allows students to create complex flood analysis and predictive hydrological modelling to protect vulnerable communities from extreme climate events (Ebrahimian & Nurrudin, 2024). Students enrolled in the MSc programme can learn these remote sensing skills and become built environment professionals who can use them to create spatial data that can be used to drive decision making in the built environment both in the industry and for government agencies.

METHODOLOGY

This study used a longitudinal descriptive study approach with quantitative feedback obtained in several semesters from 2023 to 2026 to assess the effectiveness of the remote sensing teaching innovation. The target population comprised the postgraduate students who are studying in the Master of Science (MSc) Geographical Information Science (GIS) program in the Faculty of Built Environment. The total sample size for this study was about 40 students ($n \approx 40$) over four years. Collecting data over successive cohorts helps to reduce the seasonal

influence and allows for feedback to be based on a consistent assessment of the pedagogical shifts, not a one-off event (Bissell, Robertson,McCurry and McAleer, 2018). Generally, built environment courses have limited numbers of students at the postgraduate level, which makes it useful to have multiple terms of data to build up a larger and more statistically acceptable sample size when analysed to draw conclusions about the effectiveness of educational interventions (Hennink & Kaiser, 2022).

The main data collection instrument was a structured, self-administered questionnaire which sought to gather information about a number of aspects of the student experience. The survey was broken down into three focused areas along educational measurement principles to assess specific learning outcomes. In Section 1, emphasis was placed on technical data handling, examining the students' ability to work with complex remote sensing data sets. The first section was devoted to technical data handling, testing the students' capacities in working with complex remote sensing data sets. Section 2 examined the students' adaptive problem solving and professional resilience, which included their ability to deal with challenges that arose unexpectedly to their projects. Lastly, Section 3 analyzed the overall effect of teaching innovation and career readiness and identified the role of Industry-Academy collaboration in preparing students for work. All items were taken on a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). This is very useful to convert human perceptions into quantitative data for pedagogical assessment (Joshi et al., 2022). The survey data obtained was then aggregated and analysed using IBM SPSS Statistics software, which involved calculating the mean score values for each of the items with primary focus on the mean score values (Pallant, 2020). Student responses were analysed to look for the central tendency using the arithmetic mean ($\bar{X}$) and to measure the success of the teaching innovation. The following standard equation is used to express the calculation:

$$\bar{X} = \frac{\sum_{i=1}^n X_i}{n}$$

where $\sum_{i=1}^n X_i$ represents the sum of all individual student scores for a specific questionnaire item, and n is the total number of responding students ($n = 40$). The resulting mean values were then benchmarked against a predefined descriptive scale (e.g., scores between 4.00 and 4.50 were classified as "High," and scores above 4.50 as "Very High") to systematically identify which elements of the collaborative, hands-on framework yielded the most significant educational impact (Field, 2020).

FINDINGS AND DISCUSSION

The feedback received from our cohort of 40 MSc students was very encouraging for the Section 1 with all the mean scores in the "High" or "Very High" range and no negative feedback. Students reported very high levels of confidence in responding to Item 3 (Mean = 4.63, Very High) when the results of data gathered in real-world situations did not align with perfect textbook theories. This was closely followed by Item 4, which indicated that students were ready to move from the lab setting to a large-scale, real data environments (Mean = 4.50, Very High). With regard to Item 2, students were also very confident in the use of remote sensing for real-life problems such as urban sprawl, flood mapping, and agriculture (Mean = 4.38, Very High), and were equally high (Mean = 4.25, High) in their confidence with pre-processing raw multispectral images (Table 1).

Table 1 The technical competency and data handing results from the Section 1

SECTION 1: Technical Competency & Data Handling	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)	Mean	Scale
1. I feel confident pre-processing raw multispectral imageries.	0	0	10	10	20	4.25	High
2. I can successfully apply remote sensing applications which related to environmental issues (e.g., urban development, flood mapping, vegetation/agriculture assessment).	0	0	5	15	20	4.38	Very High

3. I know how to manage data inconsistencies when field-data results do not match theoretical textbook expectations.	0	0	0	15	25	4.63	Very High
4. I understand how to transition from basic software lab exercises to large-scale, live data environments.	0	0	2	16	22	4.50	Very High

The results of these scores, particularly handling data contradictions and working with live data, indicate that working with real, imperfect data in the classroom is of great assistance in developing practical problem-solving skills. Dealing with the discrepancies in the real world as opposed to only perfect "textbook" examples is much more resilient, and we are much more independent. This is consistent with the findings of Carbonell-Carrera et al. (2021) that students learn better through direct, hands-on experience with real spatial data than they do through traditional lectures. Not to mention used wisely to solve seemingly random problems such as Malaysian floods and urban heat islands, it demonstrates that we're not just pressing buttons on software. As noted by Bissell et al. (2018), geospatial higher education must be "hired ready" by pushing students into a large-scale, real-world problem-solving environment. Overall, we are getting both the technical skills and confidence from the software training to live application so as it will be helpful for our future courses in the built environment

The questionnaire responses from the MSc student group (n=40) in Section 2 (adaptive problem-solving and professional resilience) were all very positive with all mean scores achieving the 'High' baseline scale. In particular, Item 2 had the highest agreement score (Mean = 4.20, High) where respondents indicated that they had the ability to work well on a project when its requirements changed because of real community or industry needs. (Table 2) The postgraduate students also knew how to adapt their methodology when unexpected complications arose in their data, such as poor satellite imagery captures or changing tides along the coasts (Item 1 – Mean = 4.13, High). Even if there were no step-by-step lab manual or answer key, the analysis demonstrated that students continued to feel comfortable in the process of making independent decisions based on data (Item 3, Mean = 4.00, High). The stable high outcomes demonstrate that the requirement to produce lab sheets without any academic "safety net" gives master's students valuable professional soft skills, such as flexibility and stress management. Students are exposed to challenges in the fluid, real-life context rather than to standard classroom tasks and learn to adapt their technical processes dynamically to meet the challenge. This result aligns with Azizah, Waluya and Ardiansyah (2024) who pointed out that the use of problem-based learning models in geospatial education is essential to produce graduates who are able to deal with the geographical problems that exist in the real world. Beyond this, by moving from passive learning to interactive and industry-related problem solving, Mayonita, Istiawati, Wijaya and Widodo (2026) found that higher order thinking is successfully developed and self-confidence of post graduate students in making technical decisions is boosted. Overall, the reporting data indicates that this teaching innovation is considered to be effective in preparing built environment Graduates for the actual workplace in which projects are not a simple construct and professional demands are constantly evolving.

Table 2 The adaptive problem-solving and professional resilience results from the Section 2

SECTION 2: Adaptive Problem-Solving & Professional Resilience	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)	Mean	Scale
1. When faced with unexpected data complications (e.g., changing coastal tides, poor imagery captures), I know how to adapt my methodology.	0	0	8	19	13	4.13	High
2. I can work effectively under pressure when project requirements change due to real-world community or industry demands.	0	0	7	18	15	4.20	High
3. I am comfortable making data-driven decisions when there is no step-by-step lab manual or answer key to follow.	0	0	10	20	10	4.00	High

The questionnaire responses from the MSc student group (n=40) in Section 2 (adaptive problem-solving and professional resilience) were all very positive with all mean scores achieving the 'High' baseline scale. In particular, Item 2 had the highest agreement score (Mean = 4.20, High) where respondents indicated that they had the ability to work well on a project when its requirements changed because of real community or industry needs. (Table 2) The postgraduate students also knew how to adapt their methodology when unexpected complications arose in their data, such as poor satellite imagery captures or changing tides along the coasts (Item 1 – Mean = 4.13, High). Even if there were no step-by-step lab manual or answer key, the analysis demonstrated that students continued to feel comfortable in the process of making independent decisions based on data (Item 3, Mean = 4.00, High). The stable high outcomes demonstrate that the requirement to produce lab sheets without any academic "safety net" gives master's students valuable professional soft skills, such as flexibility and stress management. Students are exposed to challenges in the fluid, real-life context rather than to standard classroom tasks and learn to adapt their technical processes dynamically to meet the challenge. This result aligns with Azizah, Waluya and Ardiansyah (2024) who pointed out that the use of problem-based learning models in geospatial education is essential to produce graduates who are able to deal with the geographical problems that exist in the real world. Beyond this, by moving from passive learning to interactive and industry-related problem solving, Mayonita et al. (2026) found that higher order thinking is successfully developed and self-confidence of post graduate students in making technical decisions is boosted. Overall, the reporting data indicates that this teaching innovation is considered to be effective in preparing built environment Graduates for the actual workplace in which projects are not a simple construct and professional demands are constantly evolving.

Table 3 The overall impact of teaching innovation and career readiness results from the Section 3

SECTION 3: Overall Impact of Teaching Innovation & Career Readiness	Strongly Disagree (1)	Disagree (2)	Neutral (3)	Agree (4)	Strongly Agree (5)	Mean	Scale
1. The two-step presentation requirement (first to industry, then to academia) significantly improved my communication versatility.	0	0	10	18	12	4.05	High
2. This collaborative approach (Academia + Industry) was more effective for my learning than traditional, lecture-only courses.	0	0	0	20	20	4.50	Very High
3. The hands-on project experience has made me feel much more prepared to enter the geospatial/geomatics workforce.	0	0	0	25	15	4.38	Very High
4. I would recommend this community/industry-engaged learning model for other advanced STEM courses.	0	0	0	22	18	4.45	Very High

CONCLUSIONS

In conclusion, feedback from the MSc student group (n=40) showed very positive results with three items being rated at the "Very High" scale and one at "High". The collaborative model (academics and industry) was seen as very effective in helping students learn, as shown in the section of the questionnaire where the highest number of students (20) agreed and 20 students strongly agreed (Item 2, Mean = 4.50, Very High). This was followed closely by Item 4 which had a Mean = 4.45 (Very High) when the respondents strongly recommended this academia/industry-engaged learning model for other advanced STEM courses. Furthermore, the practical aspects of the module definitely enhanced professional confidence with students reporting a significant increase in their professional confidence after completing the hands-on project experience (Item 3, Mean = 4.38, Very High) (Table 3). The presentation requirement where students had to pitch technical findings in the first step to industry experts was very well appreciated by the students as it led to an improvement in communication versatility across different groups (Table 3; Item 1, Mean = 4.05, High). The excellent results are obvious in these scores and indicate that such a transfer of all postgraduate learning from passive to interactive learning environments with multi-stakeholders is of enormous benefit for student development. As the curriculum brings together technical

remote sensing software processes and real-life industrial or community needs, it effectively moves master's students from being theory students to being ready to work. The result is similar to Morales-Botello and Moreno Martínez (2022) demonstrated that designing curricula around industry-demanded skills (such as problem-solving and critical thinking) within a structured framework significantly boosts students' motivation, self-efficacy, and academic engagement. Overall, the reporting results document the benefits of this innovative teaching model, not only for the development of the technical skills of remote sensing but also for the ability of built environment graduates to communicate flexibly and confidently in the workplace.

ACKNOWLEDGEMENTS

The authors wish to express their gratitude to all GES713 students who provided their feedback for this study. Special thanks also go to all the lecturers from the Department of Surveying Science and Geomatics, Faculty of Built Environment, UiTM Shah Alam

REFERENCES

1. Abekiri, N., Rachdy, A., Ajaamoum, M., Nassiri, B., Elmahni, L., & Oubail, Y. (2023). Platform for hands-on remote labs based on the ESP32 and NOD-red. *Scientific African*, 19, e01502. <https://doi.org/10.1016/j.sciaf.2022.e01502>
2. Akhtar, M. N., Ansari, E., Alhady, S. S. N., & Abu Bakar, E. (2023). Leveraging on advanced remote sensing- and artificial intelligence-based technologies to manage palm oil plantation for current global scenario: A review. *Agriculture*, 13(2), 504. <https://doi.org/10.3390/agriculture13020504>
3. Azizah, F., Waluya, S. B., & Ardiansyah, A. S. (2024). Systematic review on critical thinking through STEM integrated learning in education. *International Journal of Education in Mathematics, Science, and Technology*, 13(6), 1384–1398. <https://doi.org/10.46328/ijemst.5106>
4. Bauer, T., Immitzer, M., Mansberger, R., Vuolo, F., Márkus, B., Wojtaszek, M. V., Földvály, L., Szablowska-Midor, A., Kozak, J., Oliveira, I., van Lieshout, A., Vekerdy, Z., Ninsawat, S., & Mozumder, C. (2021). The making of a joint e-learning platform for remote sensing education: Experiences and lessons learned. *Remote Sensing*, 13(9), 1718. <https://doi.org/10.3390/rs13091718>
5. Bissell, V., Robertson, D. P., McCurry, C. W., & McAleer, J. P. G. (2018). Evaluating major curriculum change: The effect on student confidence. *British Dental Journal*, 224(7), 529–534. <https://doi.org/10.1038/sj.bdj.2018.219>
6. Carbonell-Carrera, C., Melian-Diaz, D., & Jaeger, A. J. (2021). Geospatial thinking development through geospatial technologies. *Sustainability*, 13(9), 4725. <https://doi.org/10.3390/su13094725>
7. Chasmer, L. E., Ryerson, R. A., & Coburn, C. A. (2021). Educating the next generation of remote sensing specialists: Skills and industry needs in a changing world. *Canadian Journal of Remote Sensing*, 48, 55–70. <https://doi.org/10.1080/07038992.2021.1925531>
8. DeMers, M. N., Battersby, S. E., Mitchell, J. T., & Sinton, D. S. (2021). Spatial thinking across the curriculum: Restructuring higher education for a geospatial workforce. *Journal of Geography*, 120(3), 91–101. <https://doi.org/10.1080/00221341.2021.1894563>
9. Do, T. K., Nguyen, T. H., & Vo, K. D. (2023). Experiential learning models in advanced STEM education: Structural frameworks for stakeholder collaboration. *International Journal of STEM Education*, 10(2), 145–160. <https://doi.org/10.1186/s40594-023-00412-1>
10. Ebrahimian, M., & Nurrudin, A. A. (2024). Quantitative assessment of past and future tropical forest transition and its dynamic to streamflow of the catchment, Malaysia. *iForest - Biogeosciences and Forestry*, 17, 181–191. <https://doi.org/10.3832/for4339-017>
11. Field, A. (2020). *Discovering statistics using IBM SPSS statistics* (5th ed.). SAGE Publications.
12. Ghalehtimouri, K. J., Ros, F. C., & Rambat, S. (2024). Impact of spatial planning and policies application on land transformation under the National Physical Plan regional policies in Selangor State between 2005 and 2020: a satellite-based analysis. *Regional Statistics*, 14(6), 1069–1098. <https://doi.org/10.15196/rs140603>
13. Hennink, M., & Kaiser, B. N. (2022). Sample sizes for saturation in qualitative research: A systematic review of empirical tests. *Social Science & Medicine*, 292, Article 114523. <https://doi.org/10.1016/j.socscimed.2021.114523>

14. Joshi, A., Kale, S., Chandel, S., & Pal, D. K. (2022). Likert scale: Explored and explained. *Current Journal of Applied Science and Technology*, 41(43), 1–11. <https://doi.org/10.9734/cjast/2022/v41i433983>
15. Li, J., Sheng, J., Chen, Y., Ke, L., Yao, N., Miao, Z., Zeng, X., Hu, L., & Wang, Q. (2020). A web-based learning environment of remote sensing experimental class with Python. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLIII-B5-2020, 57–61. <https://doi.org/10.5194/isprs-archives-xliii-b5-2020-57-2020>
16. Li, W., Fu, D., Su, F., & Xiao, Y. (2020). Spatial–Temporal Evolution and Analysis of the Driving Force of Oil Palm Patterns in Malaysia from 2000 to 2018. *ISPRS International Journal of Geo-Information*, 9(4), 280. <https://doi.org/10.3390/ijgi9040280>
17. Mašterová, V. (2023). Learning and teaching through inquiry with geospatial technologies: a systematic review. *European Journal of Geography*, 14, 42–54. <https://doi.org/10.48088/ejg.v.mas.14.3.042.054>
18. Mayonita, E., Istiawati, N. F., Wijaya, N. M., & Widodo, S. (2026). Fostering spatial thinking ability through problem-based learning: Evidence from senior high school geography education. *Journal Learning Geography*, 7(1), 86–103. <https://doi.org/10.23960/jlg.v7.i1.104>
19. Mendo-Lázaro, S., León-del-Barco, B., Polo-del-Río, M. I., & López-Ramos, V. M. (2022). The impact of cooperative learning on university students' academic goals. *Frontiers in Psychology*, 12, Article 787210. <https://doi.org/10.3389/fpsyg.2021.787210>
20. Mkhongi, F. A., & Musakwa, W. (2020). Perspectives of GIS education in high schools: An evaluation of uMgungundlovu district, KwaZulu-Natal, South Africa. *Education Sciences*, 10(5), 131. <https://doi.org/10.3390/educsci10050131>
21. Mohd Najib, N. E., Kanniah, K. D., Cracknell, A. P., & Yu, L. (2020). Synergy of active and passive remote sensing data for effective mapping of oil palm plantation in Malaysia. *Forests*, 11(8), 858. <https://doi.org/10.3390/f11080858>
22. Morales-Botello, M. L., & Moreno Martínez, C. (2022). Semi-guided learning tool as framework for STEM students learning: A case study for final year projects. *Education and Information Technologies*, 28, 1535–1557. <https://doi.org/10.1007/s10639-022-11231-0>
23. Nuthammachot, N. (2022). Exploring Sentinel-2 satellite imagery-based vegetation indices for classifying healthy and diseased oil palm trees. *Journal of Oil Palm Research*, 34. <https://doi.org/10.21894/jopr.2022.0068>
24. Pallant, J. (2020). *SPSS survival manual: A step-by-step guide to data analysis using IBM SPSS* (7th ed.). Routledge.